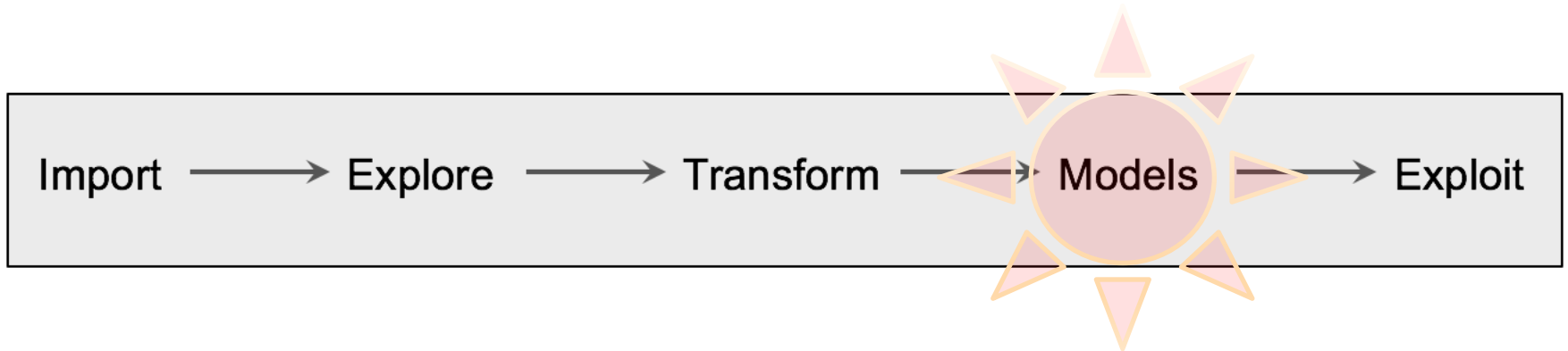


# The Pipeline



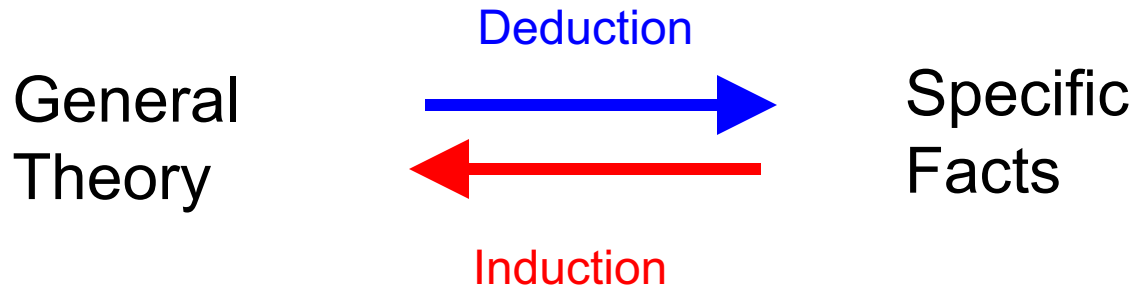
- We have looked at importing, exploring and transforming data.
- Now it is time to do something with our data: **MODELS!**
- Here we discuss one of the most straight forward machine learning models: **the decision tree.**

# Machine Learning

- What is Machine Learning?
  - Programs that get better with *experience* given a *task* and some *performance measure*.
    - Learning to classify news articles
    - Learning to recognize spoken words
    - Learning to play board games
    - Learning to navigate (e.g. self-driving cars)
- Usually involves some sort of inductive reasoning step.

# Inductive Reasoning

- Deductive reasoning (rule based reasoning)
  - From the general to the specific
- Inductive reasoning
  - From the specific to the general



**Note:** not to be confused with mathematical induction!

# Example - Deduction

- Rules:
  - If Betty wears a white dress then it is Sunday.
  - Betty wears a white dress.
- Deductive step:
  - You infer or *deduce* that today is Sunday.

If Betty wears a white dress then it is Sunday.  
Betty wears a white dress.



Today is Sunday.

Deduction

**Inference** is the act or process of drawing a conclusion based solely on what one already knows.

# Example - Induction

- Facts: every time you see a swan you notice that the swan is white.
- Inductive step: you infer that all swans are white.

All Swans  
are white.



Induction

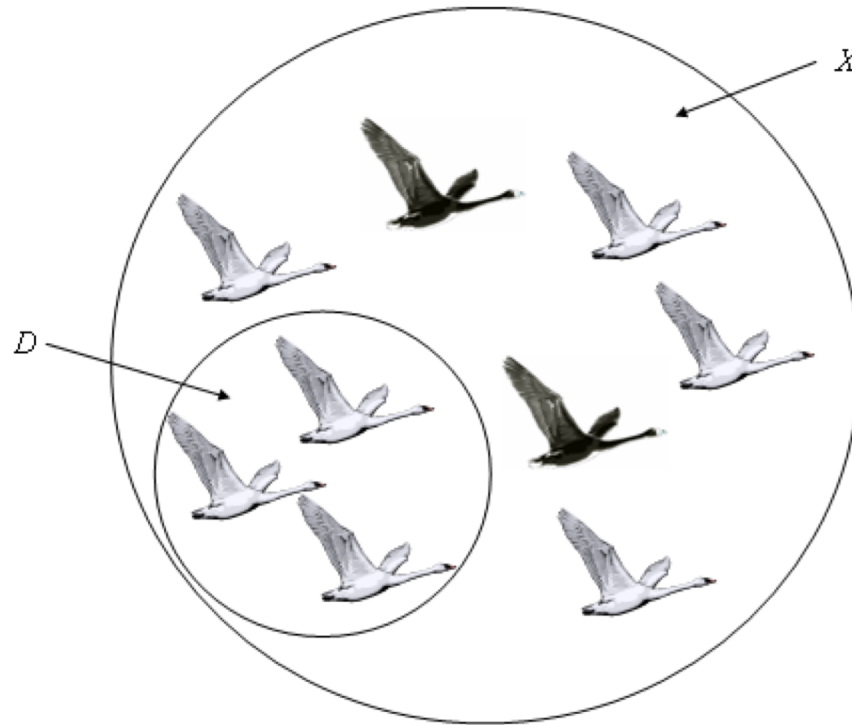
Observed Swans  
are white.

**Inference** is the act or process of drawing a conclusion based solely on what one already knows.

# Observation

- Deduction is “truth preserving”
  - If the rules employed in the deductive reasoning process are sound, then, what holds in the theory will hold for the deduced facts.
- Induction is NOT “truth preserving”
  - It is more of a statistical argument
  - The more swans you see that are white, the more probable it is that all swans are white..  
**But this does not exclude the existence of black swans**

# Observation



$D \equiv$  observations

$X \equiv$  universe of all swans

# Different Styles of Machine Learning

- Supervised Learning
  - The learning needs explicit examples of the concept to be learned (e.g. white swans, playing tennis, *etc*)
- Unsupervised Learning
  - The learner discovers autonomously any structure in a domain that might represent an interesting concept



# Knowledge - Representing what has been learned

- Symbolic Learners (transparent models)
  - If-then-else rules
  - Decision trees
  - Association rules
- Sub-Symbolic Learners (non-transparent models)
  - (Deep) Neural Networks
  - Clustering (Self-Organizing Maps, k-Means)
  - Support Vector Machines

# Decision Trees

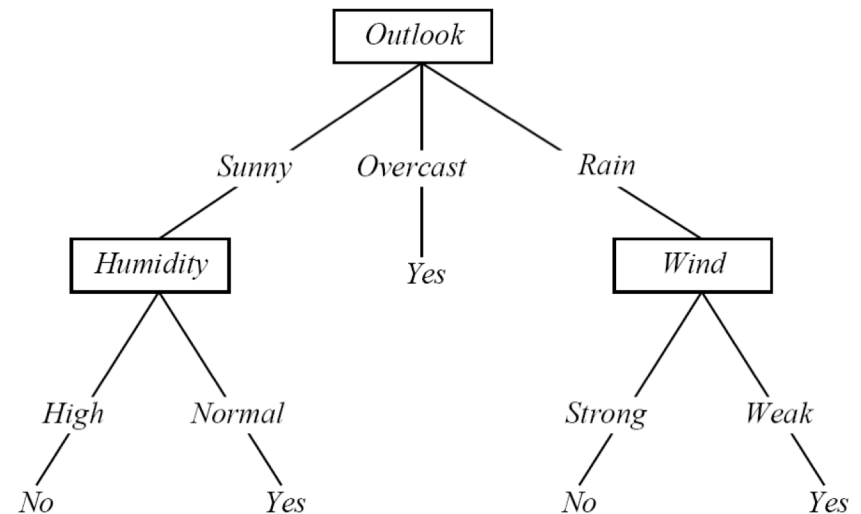
- Learn from labeled observations - supervised learning
- Represent the knowledge learned in form of a tree

Example: learning when to play tennis.

- Examples/observations are days with their observed characteristics and whether we played tennis or not

# Play Tennis Example

Outlook	Temperature	Humidity	Windy	PlayTennis
Sunny	Hot	High	False	No
Sunny	Hot	High	True	No
Overcast	Hot	High	False	Yes
Rainy	Mild	High	False	Yes
Rainy	Cool	Normal	False	Yes
Rainy	Cool	Normal	True	No
Overcast	Cool	Normal	True	Yes
Sunny	Mild	High	False	No
Sunny	Cool	Normal	False	Yes
Rainy	Mild	Normal	False	Yes
Sunny	Mild	Normal	True	Yes
Overcast	Mild	High	True	Yes
Overcast	Hot	Normal	False	Yes
Rainy	Mild	High	True	No



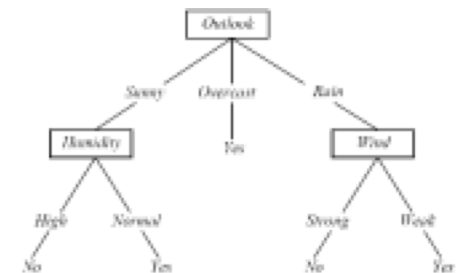
# Decision Tree Learning

Outlook	Temperature	Humidity	Windy	PlayTennis
Sunny	Hot	High	False	No
Sunny	Hot	High	True	No
Overcast	Hot	High	False	Yes
Rainy	Mild	High	False	Yes
Rainy	Cool	Normal	False	Yes
Rainy	Cool	Normal	True	No
Overcast	Cool	Normal	True	Yes
Sunny	Mild	High	False	No
Sunny	Cool	Normal	False	Yes
Rainy	Mild	Normal	False	Yes
Sunny	Mild	Normal	True	Yes
Overcast	Mild	High	True	Yes
Overcast	Hot	Normal	False	Yes
Rainy	Mild	High	True	No

Facts or Observations



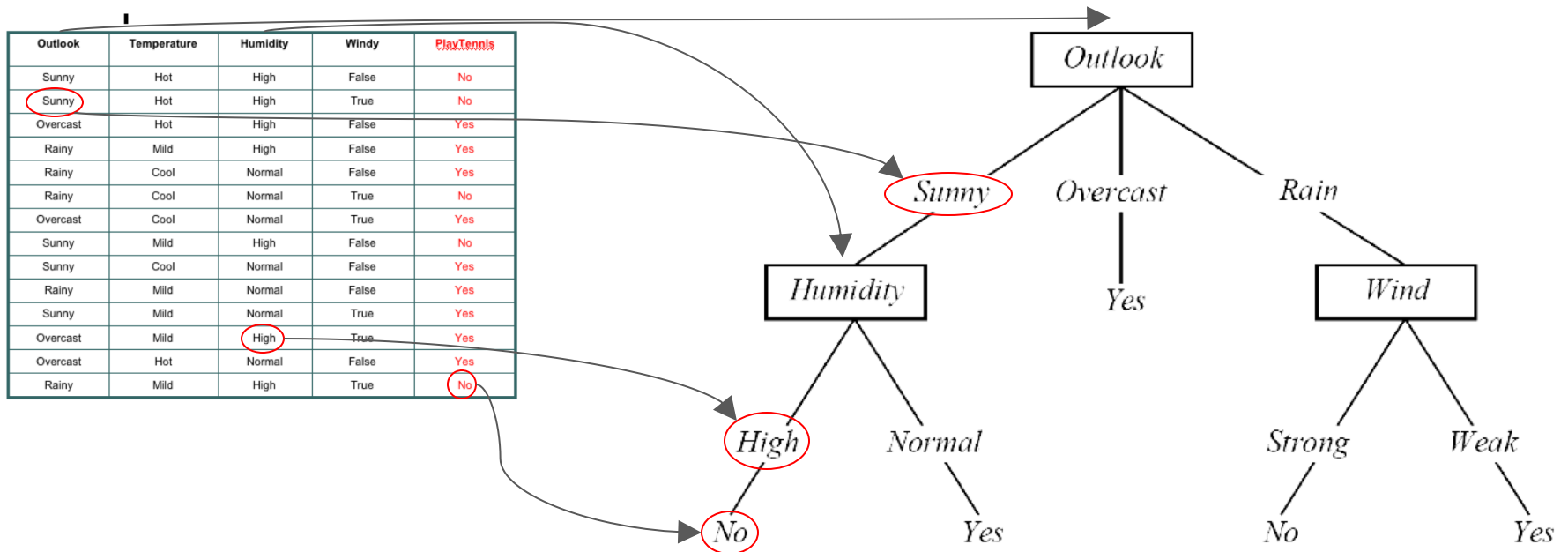
Induction



Theory

# Interpreting a DT

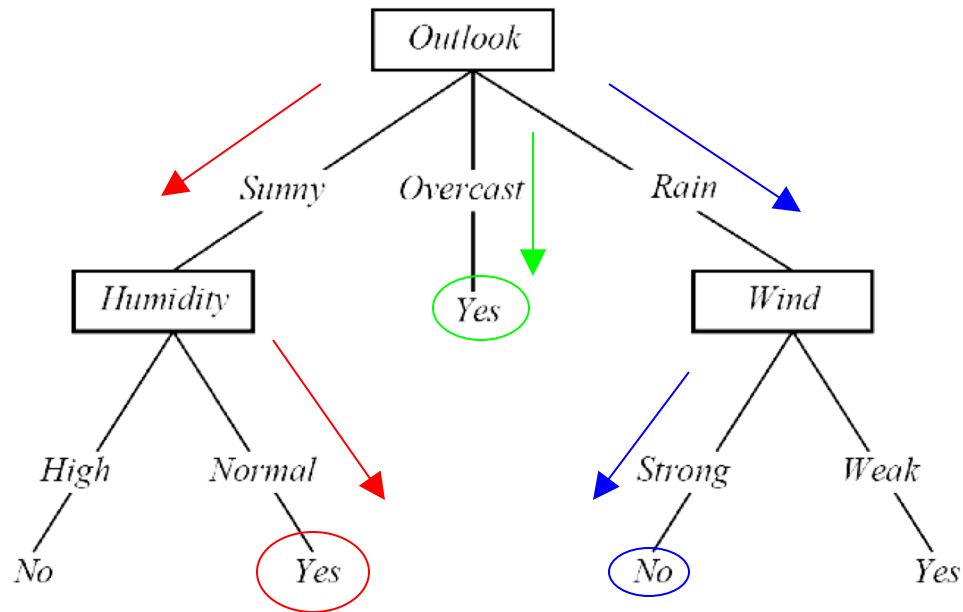
DT  $\equiv$  Decision  
Tree



- A DT uses the features of an observation table as nodes and the feature values as links.
- All feature values of a particular feature need to be represented as links.
- The target feature is special - its values show up as leaf nodes in the DT.

# Interpreting a DT

Each path from the root of the DT to a leaf can be interpreted as a decision rule.



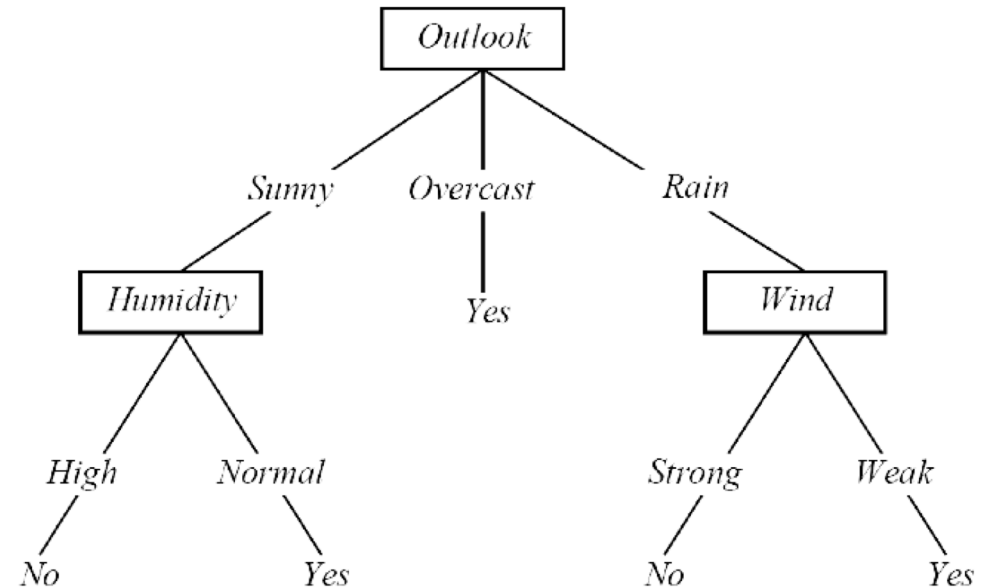
IF *Outlook = Sunny* AND *Humidity = Normal* THEN *Playtennis = Yes*

IF *Outlook = Overcast* THEN *Playtennis = Yes*

IF *Outlook = Rain* AND *Wind = Strong* THEN *Playtennis = No*

# DT: Explanation & Prediction

Outlook	Temperature	Humidity	Windy	PlayTennis
Sunny	Hot	High	False	No
Sunny	Hot	High	True	No
Overcast	Hot	High	False	Yes
Rainy	Mild	High	False	Yes
Rainy	Cool	Normal	False	Yes
Rainy	Cool	Normal	True	No
Overcast	Cool	Normal	True	Yes
Sunny	Mild	High	False	No
Sunny	Cool	Normal	False	Yes
Rainy	Mild	Normal	False	Yes
Sunny	Mild	Normal	True	Yes
Overcast	Mild	High	True	Yes
Overcast	Hot	Normal	False	Yes
Rainy	Mild	High	True	No



Explanation: the DT summarizes (explains) all the observations in the table perfectly  $\Rightarrow$  100% Accuracy

Prediction: once we have a DT (or model) we can use it to make predictions on observations that are not in the original training table, consider:

Outlook = Sunny, Temperature = Mild, Humidity = Normal, Windy = False, Playtennis = ?

# Constructing DTs

- How do we choose the attributes and the order in which they appear in a DT?
  - Recursive partitioning of the original data table
  - Heuristic - each generated partition has to be “less random” (entropy reduction) than previously generated partitions



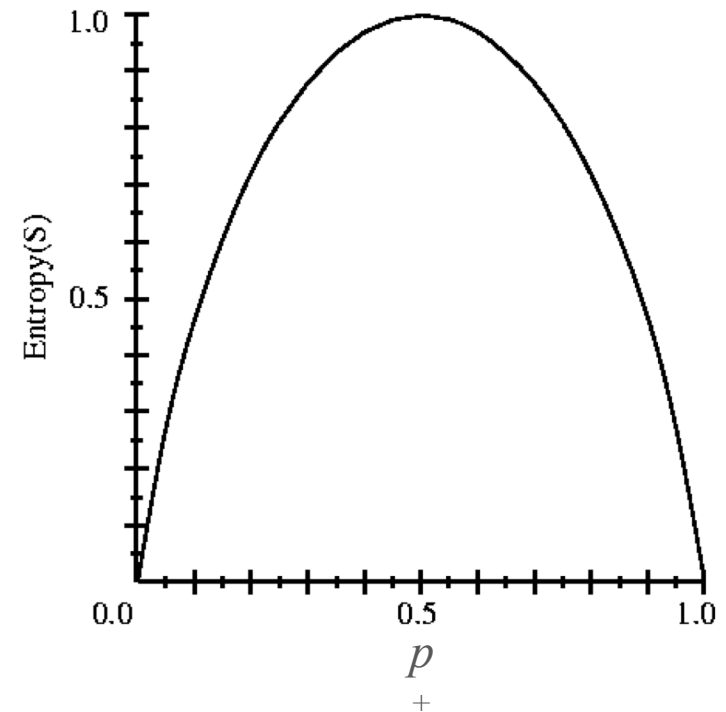
# Entropy

- $S$  is a sample of training examples
- $p^+$  is the proportion of positive examples in  $S$
- $p^-$  is the proportion of negative examples in  $S$
- Entropy measures the impurity (randomness) of  $S$

$S$  {

Outlook	Temperature	Humidity	Windy	PlayTennis
Sunny	Hot	High	False	No
Sunny	Hot	High	True	No
Overcast	Hot	High	False	Yes
Rainy	Mild	High	False	Yes
Rainy	Cool	Normal	False	Yes
Rainy	Cool	Normal	True	No
Overcast	Cool	Normal	True	Yes
Sunny	Mild	High	False	No
Sunny	Cool	Normal	False	Yes
Rainy	Mild	Normal	False	Yes
Sunny	Mild	Normal	True	Yes
Overcast	Mild	High	True	Yes
Overcast	Hot	Normal	False	Yes
Rainy	Mild	High	True	No

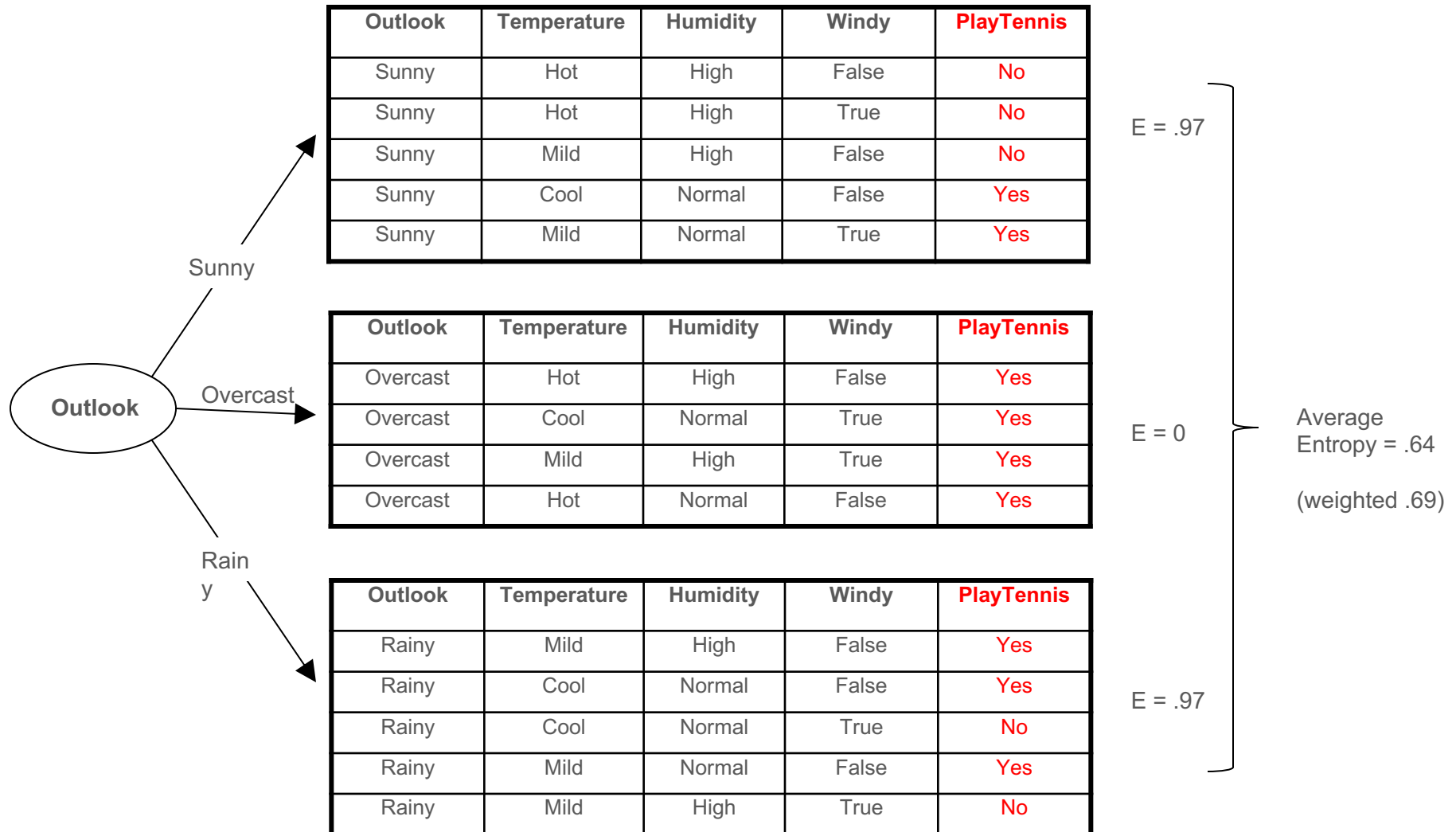
$$Entropy(S) = Entropy([9+,5-]) = .94$$



$$\square Entropy(S) \equiv -p^+ \log_2 p^+ - p^- \log_2 p^-$$

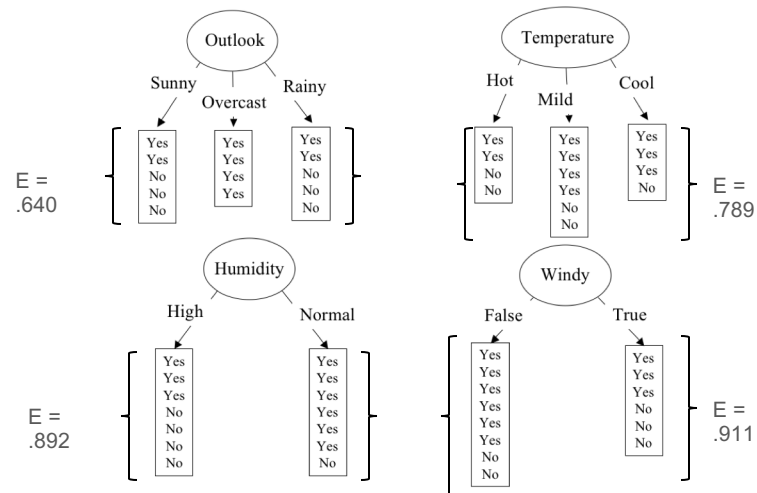
$$\text{AvgEntropy}(S, A) = \sum_{v \in \text{Values}(A)} \frac{|S_v|}{|S|} E(S_v) \quad (\text{weighted average})$$

# Partitioning the Data Set



# Partitioning in Action

Outlook	Temperature	Humidity	Windy	PlayTennis
Sunny	Hot	High	False	No
Sunny	Hot	High	True	No
Overcast	Hot	High	False	Yes
Rainy	Mild	High	False	Yes
Rainy	Cool	Normal	False	Yes
Rainy	Cool	Normal	True	No
Overcast	Cool	Normal	True	Yes
Sunny	Mild	High	False	No
Sunny	Cool	Normal	False	Yes
Rainy	Mild	Normal	False	Yes
Sunny	Mild	Normal	True	Yes
Overcast	Mild	High	True	Yes
Overcast	Hot	Normal	False	Yes
Rainy	Mild	High	True	No



# Recursive Partitioning

Partition(*Examples*, *TargetAttribute*, *Attributes*)

*Examples* are the training examples. *TargetAttribute* is a binary (+/-) categorical dependent variable and *Attributes* is the list of independent variables which are available for testing at this point. This function returns a decision tree.

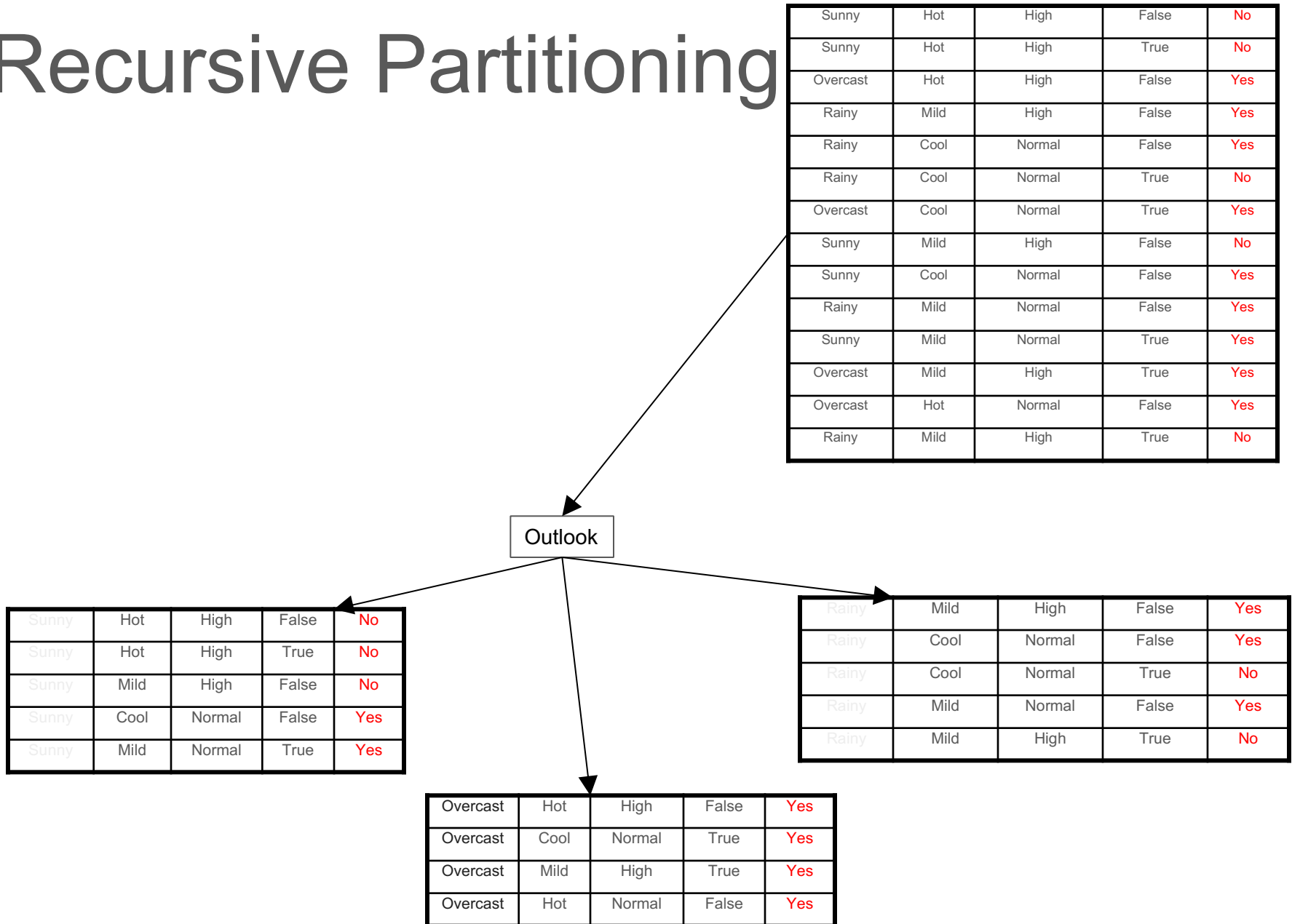
- Create a *Root* node for the tree.
- If all *Examples* are positive then return *Root* as a leaf node with label = +.
- Else if all *Examples* are negative then return *Root* as a leaf node with label = -.
- Else if *Attributes* is empty then return *Root* as a leaf node with label = most common value of *TargetAttribute* in *Examples*.
- Otherwise
  - $A :=$  the attribute from *Attributes* that reduces entropy the most on the *Examples*.
  - $Root := A$
  - For each  $v \in \text{values}(A)$ 
    - Add a new branch below the *Root* node with value  $A = v$
    - Let  $Examples_v$  be the subset of *Examples* where  $A = v$
    - If  $Examples_v$  is empty then add new leaf node to branch with label = most common value of *TargetAttribute* in *Examples*.
    - Else add new subtree to branch  
Partition( $Examples_v$ , *TargetAttribute*,  $Attributes - \{A\}$ )
- Return *Root*

# Recursive Partitioning

Our data set:

Outlook	Temperature	Humidity	Windy	PlayTennis
Sunny	Hot	High	False	No
Sunny	Hot	High	True	No
Overcast	Hot	High	False	Yes
Rainy	Mild	High	False	Yes
Rainy	Cool	Normal	False	Yes
Rainy	Cool	Normal	True	No
Overcast	Cool	Normal	True	Yes
Sunny	Mild	High	False	No
Sunny	Cool	Normal	False	Yes
Rainy	Mild	Normal	False	Yes
Sunny	Mild	Normal	True	Yes
Overcast	Mild	High	True	Yes
Overcast	Hot	Normal	False	Yes
Rainy	Mild	High	True	No

# Recursive Partitioning



# Recursive Partitioning

Outlook

Sunny	Hot	High	False	No
Sunny	Hot	High	True	No
Sunny	Mild	High	False	No
Sunny	Cool	Normal	False	Yes
Sunny	Mild	Normal	True	Yes

Rainy	Mild	High	False	Yes
Rainy	Cool	Normal	False	Yes
Rainy	Cool	Normal	True	No
Rainy	Mild	Normal	False	Yes
Rainy	Mild	High	True	No

Overcast	Hot	High	False	Yes
Overcast	Cool	Normal	True	Yes
Overcast	Mild	High	True	Yes
Overcast	Hot	Normal	False	Yes

# Recursive Partitioning

Outlook

Sunny	Hot	High	False	No
Sunny	Hot	High	True	No
Sunny	Mild	High	False	No
Sunny	Cool	Normal	False	Yes
Sunny	Mild	Normal	True	Yes

Rainy	Mild	High	False	Yes
Rainy	Cool	Normal	False	Yes
Rainy	Cool	Normal	True	No
Rainy	Mild	Normal	False	Yes
Rainy	Mild	High	True	No

Overcast	Hot	High	False	Yes
Overcast	Cool	Normal	True	Yes
Overcast	Mild	High	True	Yes
Overcast	Hot	Normal	False	Yes

Humidity

Sunny	Cool	Normal	False	Yes
Sunny	Mild	Normal	True	Yes

Sunny	Hot	High	False	No
Sunny	Hot	High	True	No
Sunny	Mild	High	False	No



# Recursive Partitioning

Outlook

Sunny	Hot	High	False	No
Sunny	Hot	High	True	No
Sunny	Mild	High	False	No
Sunny	Cool	Normal	False	Yes
Sunny	Mild	Normal	True	Yes

Humidity

Overcast	Hot	High	False	Yes
Overcast	Cool	Normal	True	Yes
Overcast	Mild	High	True	Yes
Overcast	Hot	Normal	False	Yes

Sunny	Cool	Normal	False	Yes
Sunny	Mild	Normal	True	Yes

Rainy	Mild	High	False	Yes
Rainy	Cool	Normal	False	Yes
Rainy	Cool	Normal	True	No
Rainy	Mild	Normal	False	Yes
Rainy	Mild	High	True	No

Windy

Rainy	Mild	High	False	Yes
Rainy	Cool	Normal	False	Yes
Rainy	Mild	Normal	False	Yes

Rainy	Cool	Normal	True	No
Rainy	Mild	High	True	No

Sunny	Hot	High	False	No
Sunny	Hot	High	True	No
Sunny	Mild	High	False	No

# Machine Learning in Python - Scikit-Learn

- We will be using the Scikit-Learn module to build decision trees.
  - Scikit-learn or sklearn for short provides all kinds of models
    - Neural networks
    - Support vector machines
    - Clustering algorithms
    - Linear regression
    - *etc*
- We will be using the treeviz module to visualize decision trees.
  - A simple ASCII based tree visualizer

# SKlearn Decision Tree Basics

Training data needs to be structured into a *feature matrix* and a *target vector*.

In the feature matrix one row for each observations.

In the target vector one entry for each observation.

NOTE: rows and vector entries have to be consistent!

